Hidden Sentiment Behind Letter Repetition in Online Reviews

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***Abstract*—Minimal research has been done on how letter repetition affects readers' perception of expressed sentiment within a text. To the best of the researchers' knowledge, no studies have tested samples of text with letter repetition using sentiment tools. The main aim of this paper is to investigate whether letter repetition in product reviews are perceived to have any sentiment value, based on ratings by individual participants and analyses using sentiment tools. This study collected and analyzed 1,041 consumer reviews in the form of online comments using the UCREL Wmatrix system, and simulated emotional words within the comments to contain repeated letters. A group of 500 participants rated 15 positive comments and 15 negative comments and their respective simulated counterparts, while 32 sentiment tools are used to analyze a pair of positive comment and its simulated counterpart and a pair of negative comment and its simulated counterpart. Results indicate that readers perceive letter repetition to amplify a comment's sentiment value, in which the effect was found more strongly in negative comments than positive comments. On the other hand, analyses using sentiment tools show that a majority of these tools are unable to detect letter repetition within a word and instead, treats the word as a spelling mistake. As consumers or online users in general have been found to use letter repetition to intensify and express their sentiments in their comments, this study's findings suggest that letter repetition processing in any text-based mechanism needs to be enhanced. The outcome of this paper is useful for improving the measurement of sentiment analysis for the use of marketing applications.**

***Index Terms*— Computer-Mediated Communication (CMC); Letter Repetition; Online Reviews; Product Reviews; Sentiment Tools; Text-Based Cue.**

I. Introduction

Social media text, such as Twitter posts and product reviews, often contains a variety of non-verbal and non-grammatical codes and symbols including exclamation marks, emoticons, and letter repetition. Such symbols are usually used to express mood, intonation, and emphasis that are ignored or difficult to convey in the text [1]. Past researchers found that letter repetition defined as a paralinguistic cue in relaying non-verbal communication via computer-mediated channels [2][3]. For example, Carey[2] observed that paralinguistic features and concluded that people find it important to outline tonal and expressive information even if such information is difficult to convey. Carey[2] categorized the usage of repeated letters as vocal spelling (e.g., "weeeeell" and "breakkk"), lexical and vocal surrogates (e.g., "Boo, boo Horror of horrors!...", "uh huh" and "hmmm").

Another study by Darics [4] also examined the specific use of letter repetition in conveying socio-emotional messages and evoking auditory cues through a single letter repetition. This is a common phenomenon in social media platforms like Twitter [5], identifyi ndings of the aforementioned research, letter repetition usage is prevalent and may play a role sentiment analysis of online product or service reviews.

This study examines letter repetition usage in product reviews and how it affects readers' perception of positive and negative sentiment in online comments on commercial products. The study's primary goal is to investigate whether there is a significant difference in sentiment ng real expressed meaning of the letter repetition accurately have a significant contribution to the understanding of sentiment in the text. As shown in the fi

expression when letter repetition is used. The focus is particularly on letter repetition within the most sentimentally expressive word in the statement. Additionally, the study also examines the accuracy of available online sentiment tools in letter repetition detection. A sample of reviews is tested on 32 sentiment tools are used to explore how these tools reflect letter repetition in their sentiment scores. Findings from this study contribute to the accurate detection and measurement of consumers' preferences and attitudes to commercial products, which is key to understanding online consumers' behavior.

II. Literature Review

Several studies on online language found that the usage of letter repetition increases when emotionally-laden interjections are employed. Kalman and Gergle [5]–[7] suggested that repeated letters and punctuations indicate the stretching of a word, emulating a stretched-out syllable of how words are articulated in a spoken conversation (e.g., "It is sweeeeeeet" and "Whaaaassssupppp"). It was found that vowels are repeated more often than consonants on average, and that letter repetition functions to denote a change in pitch (e.g., "Yeeeeeeeeehaaaw!!!!!!!!!!"), decrease in voice volume (e.g., "sshhhhhh......"), a pause (e.g. "Hmmmm"), or sounds (e.g. "vvvvrrrrroooooommmmm," "pfffffff," "Heeeeheeee!", "ugggghhhh!!!", and "Happy birthday to

This is accepted version of manuscript, please find published version at: http://journal.utem.edu.my/index.php/jtec/article/view/4721/3466

youuuu") [7]. Besides communicating pitch, tempo, and prosody, letter repetitions also feature other paralinguistic elements that focus on achieving visual emphasis (e.g., "lllllllllllllllllooooooooooooooooooooovvvvvvvvvvvvvvvvvvv veeeeeeeeeeeeeeeee") [7]. Moreover, Kalman and Gergle [5] sought to categorize letter repetition cues according to four major classifications: (a) whether they were articulable or not (e.g., "lllloooonnnngggg" and "russsssshhhh"); (b) whether they represented words in other languages, slangs, abbreviations, or acronyms not found in the dictionary (e.g., "gonna"); (c) whether they were onomatopoeic words — words that imitate sounds (e.g., "boom" or "grrr"); and (d) whether they can be attributed to the name of the message's sender name or e-mail address. These initial studies emphasize the prevalent usage of letter repetition and how it may play a strong pragmatic role in online product or service reviews. For instance, letter repetition in messages are often found to be heavy with emotionally-laden interjections (e.g., "ooops") [7] and may imitate phoneme extension found in a spoken conversation (e.g., "soooo") [5]. These cues are used to express information beyond the literal meaning of the message, suggesting a pragmatic intention not present in the words themselves.

III. METHOD

A. *Survey Set-Up*

This study collected a total of 1,041 online review comments from different social media platforms, including Amazon, e-Bay, Facebook, and GSM Arena. These reviews are taken from the following product categories [1]: (a) Beauty and Health; (b) Camera; (c) Computer; (d) Consumer Electronics; (e) Fashion; (f) Home Appliances; (g) Jewelry and Watches; (h) Mobile and Tablets; (i) Sporting Goods; and (j) Toys and Kids. Other studies have used this same dataset but for different research purposes, such as finding the most accurate machine learning classifier [8], processing emoticons [9], and exploring how emoticons and punctuations are used in online reviews [10]. The current study focuses on usage of letter repetition and understanding the changes in polarity after simulation of letter repetition.

The collected reviews are analyzed using the UCREL Wmatrix system [11] to extract emotional words that appeared most frequently. This resulted in the selection of 30 comments comprising 15 positive comments and 15 negative comments. These comments are then simulated with letter repetition, whereby a vowel within one key word for each comment is randomly selected and repeated in patterns that frequently occur in social media messages. The original comments and simulated comments of a positive nature are shown in Table 1 while those of a negative nature are shown in Table 2. The simulation was performed to test how it affects polarity when letter repetition is used in text. Following that, five hundred participants were requested to rate simulated text scaling from 1-"Strongly Dislike" to 7-"Strongly Like". Participants were chosen based on random sampling within Subang Jaya district, Malaysia, with a various age range. All of the participants have experience in reading and writing online reviews.

Table 1
Positive Samples of Comments with Repeated Letter

Text	Simulated text with letter repetition
I love it	I looooooove it
I like it	I liiiiiiiiiike it
I am very happy	I am very haaaaaappy
I am glad	I am glaaaaaaaad
I am big fan	I am big faaaaaaaan
My favorite	My faaaaaaaaavorite
Hours of fun	Hours of fuuuuuuun
Very satisfied	Very saaaaaaatisfied
I prefer it	I preeeeeeeeefer it
Really enjoy	Really eeeeeeeeenjoy
I recommend it	I recommeeeeeeeend it
Exceed expectations	Exceeeeeeeeeeed expectations
I will continue taking this brand	I will continue taking this braaaaaaaand
Are you kidding me?	Are you kidding meeeee?
No need to say more	Noooooo need to say more

Table 2
Negative Samples of Comments with Repeated Letter

Text	Simulated text with letter repetition
Some serious abuse	Some serious abuuuuuuuuse
Very disappointed	Very disappoooooooointed
I don't care	I don't caaaaaaaaare
I did hit it well	I did hiiiiiiiiit well
I hate it	I haaaaaaaaate it
It is really annoying	It is really annoooooooying
I boot it	I booooooooot it
Too much trouble	Too much trooooooouble
Totally fierce	Totally fierceeeeeeee
I have to worry	I have to wooooooooooooorry
I can afford it	I caaaaaaaan afford it.
What a lie	Whaaaaaaaat a lie
Don't come here to shop	Don't cooooooome here to shop
Fine until it breaks	Fiiiiiiiiine until it breaks
Never, ever, never	Never, ever, neeeeeeever

B. *Sentiment Tools' Set-Up*

Numerous sentiment tools are available online for various research analyses. For instance, SentiStrength analyzes short informal text [12] while TensiStrength is used to detect relaxation magnitude in social media text [13]. This study selected 32 freely available online sentiment tools (Table 3) to explore how they detect and reflect letter repetition in their sentiment scores.

Table 3
Sample for Sentiment Tools Testing

No*	Name of Sentiment Tool	Web Source
1	Selasdia Intelligent Sales Assistant	http://www.aiaioo.com:8080/annotator-0.1/automation/demoView/1
2	Sentaero	http://www.sentaero.com/textsearch.php
3	Meaning cloud	http://www.meaningcloud.com/demo
4	TheySay	http://apidemo.theysay.io/
5	Repustate	https://www.repustate.com/api-demo/
6	Text sentiment analyzer	http://werfamous.com/sentimentanalyzer
7	MIOPIA Supervised Model	http://miopia.grupolys.org/demo
8	SentiStrength	http://sentistrength.wlv.ac.uk/
9	Python NLTK Demos for Natural Language: Text Processing	http://text-processing.com/demo/

10	Text scoring: WordNet	http://sentiment.christopherpotts.net/lexicon/textscores_results/
11	Text scoring: SentiWorsNet	http://sentiment.christopherpotts.net/lexicon/textscores_results/
12	Text scoring: Opinion Lexicon	http://sentiment.christopherpotts.net/lexicon/textscores_results/
13	Text scoring: MPQA	http://sentiment.christopherpotts.net/lexicon/textscores_results/
14	Text scoring: IMDB	http://sentiment.christopherpotts.net/lexicon/textscores_results/
15	LIWC	http://liwc.wpengine.com/
16	Sentiment Analyzer	http://www.danielsoper.com/sentimentanalysis/#
17	Sentiment Analysis: Opinion mining	http://text2data.org/Demo
18	Pattern Sentiment Analysis	http://textanalysisonline.com/pattern-sentiment-analysis
19	Sentiment Vivekn [14]	http://sentiment.vivekn.com/
20	Alchemy Language Document Sentiment	https://alchemy-language-demo.mybluemix.net/
21	Alchemy Language Targeted Emotion	https://alchemy-language-demo.mybluemix.net/
22	Intellexer	http://demo.intellexer.com/
23	ParallelDots	http://www.paralleldots.com/sentiment-analysis
24	DepecheMood	http://www.depechemood.eu/DepecheMood.html
25	Twinword	https://www.twinword.com/api/sentiment-analysis.php
26	uClassify	https://www.uclassify.com/browse/uclassify/sentiment?input=Text
27	Tone Analyzer	https://tone-analyzer-demo.mybluemix.net/
28	Pythia Semantic Features	http://omiotis.hua.gr/pythia/#
29	Pythia Term n-grams	http://omiotis.hua.gr/pythia/#
30	Pythia Character n-grams	http://omiotis.hua.gr/pythia/#
31	Pythia All n-grams	http://omiotis.hua.gr/pythia/#
32	Pythia All Features	http://omiotis.hua.gr/pythia/#

*Numbers of the tools are same for the Table 3, Table 8 and Table 9.

From the 1,041 online review comments, a positive comment and a negative comment are selected to be analyzed by the sentiment tools. Letter repetition is again simulated in one key word for each sentence to check for differences in scores between the original comment and the simulated comment with repeated letters. These comments analyzed by the sentiment tools are depicted in Table 4.

Table 4
Sample for Sentiment Tools' Testing

Positive text	
Format of Text	Example used in experiment
Text without letter repetition	love our new tv. the tv is so light and thin it has a great picture and the colors are true very happy customer
Text with letter repetition	looooooove our new tv. the tv is so light and thin it has a great picture and the colors are true very happy customer
Negative Text	
Text without letter repetition	i hated this iron because the steam comes out in all the wrong places. i burnt my fingers a lot
Text with letter repetition	i haaaaaaated this iron because the steam comes out in all the wrong places. i burnt my fingers a lot

IV. RESULTS AND DISCUSSION

A. Survey Analysis

To examine the impact of letter repetition in sentiment analysis of online product reviews, the researchers invited 500 participants to rate the intensity and polarity of the sentiment of the 30 comments and their simulated counterparts. A 7-point Likert Scale [15] ranging from "Strongly Dislike" to "Strongly Like" is used to rate the comments. The difference in sentiment rating between each original comment and its simulated counterpart is also recorded. The results of the ratings for positive comments and negative comments are shown in Table 5 and Table 6 respectively. The term "increase" means that the ratings shifted towards "Strongly Like" while the term "decrease" means that the ratings shifted towards "Strongly Dislike".

As shown in Table 5, there is an average of 50.68% increment in ratings between the original comments and their simulated version. In our case, term "increase" means that the rating shifts towards "Strongly Like" value and term "decrease" means that the rating shifts towards "Strongly Dislike" value. This indicates that participants found the simulated comments to have a higher intensity in positive sentiment than their original text. For example, some participants rated "I am very happy" as only "Slightly Like" but rated "I am very haaaaaaappy" as "Like" or "Strongly Like". The pair of positive comments that underwent the largest increase in ratings is "Really enjoy" and "Really eeeeeeeeeenjoy", of which 62.2% of participants increased their ratings for the latter comment towards "Like". Overall, approximately 31% to 62% of participants increased their "Like" rating for the simulated version.

Table 5
Rating Changes in Positive Comments

Positive Comment	Rating *increases* from Original Comment to Simulated Comment	Rating *decreases* from Original Comment to Simulated Comment	Rating *maintains* from Original Comment to Simulated Comment
Really enjoy	62.2%	23.8%	14.0%
I love it	61.2%	18.0%	20.8%
My favorite	59.6%	23.4%	17.0%
I prefer it	58.4%	24.8%	16.8%
I am very happy	58.0%	26.4%	15.6%
I am glad	56.4%	21.0%	22.6%
I recommend it	54.8%	26.0%	19.2%
I will continue taking this brand	54.4%	24.0%	21.6%
Hours of fun	51.8%	16.8%	31.4%
I can afford it	49.8%	24.0%	26.2%
Exceed expectations	44.8%	30.8%	24.4%
Very satisfied	43.4%	26.6%	30.0%
I like it	39.8%	32.0%	28.2%
No need to say more	34.6%	36.0%	29.4%
I am big fan	31.0%	23.6%	45.4%
Average:	50.68%	25.15%	24.17%

For negative comments, Table 6 shows that there is an average of 60.23% decrement in ratings between the original comments and their simulated versions. This indicates that participants found the simulated comments to have a higher intensity in negative sentiment than their original versions.

disappointed			
Never, ever, never	20.0%	56.2%	23.8%
I did hit it well	19.8%	55.0%	25.2%
I hate it	13.4%	52.8%	33.8%
Totally fierce	16.0%	51.6%	32.4%
I boot it	21.8%	51.2%	27.0%
Average:	15.96%	60.23%	23.81%

For example, some participants rated “What a lie” as “Slightly Dislike” but rated “Whaaaaaaaat a lie” as “Dislike” or “Strongly Dislike”. The pair of negative comments that had the largest decrease in ratings is “I don’t care” and “I don't caaaaaaaaaare”, of which 69.6% of participants decreased their ratings for the simulated comments towards “Slightly Dislike”. Overall, with the approximately 50% to 70% of participants decreased their ratings for the simulated comments. To sum up, letter repetition has a stronger amplifying effect on the sentiment value of negative comments compared to positive ones.

Table 6
Rating Changes in Negative Comments

Negative Comment	Rating *increases* from Original Comment to Simulated Comment	Rating *decreases* from Original Comment to Simulated Comment	Rating *maintains* from Original Comment to Simulated Comment
I don't care	11.4%	69.6%	19.0%
Some serious abuse	10.8%	67.2%	22.0%
Fine until it breaks	10.6%	66.2%	23.2%
Too much trouble	18.2%	65.6%	16.2%
Don't come here to shop	11.2%	65.6%	23.2%
It is really annoying	19.0%	64.0%	17.0%
I have to worry	17.8%	62.6%	19.6%
Are you kidding me?	17.0%	59.8%	23.2%
What a lie	15.6%	58.8%	25.6%
Very	16.8%	57.2%	26.0%

Table 7 shows the mode, median, and mean ratings between positive and negative comments. Comments are considered to be significantly affected when they meet one of the following criteria: (a) Positive comments that underwent positive changes (stronger “Like” tendency) or (b) Negative comments that underwent negative changes (stronger “Dislike” tendency).

As shown in Table 7, there is a consistent and noticeable shift towards “Dislike” tendency in all three measures of central tendency for negative comments as compared to the shift towards “Like” tendency for positive comments. Among the three measures, the median is found to be the most reliable measurement because it measures the middle score for a set of data that has been sorted by magnitude, such as the ordinal Likert scale ranging from 1 to 7. Furthermore, the median is also less affected by outliers and skewed data. Therefore, when all three measures of central tendency are compared, the median displays the largest difference for some positive and negative comments that are significantly affected by repeated letter simulation. All of the negative comments experienced stronger “Dislike” tendency whereas only two-thirds of the positive comments experienced stronger “Like” tendency. This observation further confirms the earlier finding that letter repetition has a greater augmenting effect on negative comments compared to positive ones.

Table 7
Rating Changes in Positive Comments

	Positive			Negative		
	Mode ratings	Median ratings	Mean ratings	Mode ratings	Median ratings	Mean ratings
Positive changes (Higher “like” tendency)	13	10	14	0	0	0
Negative changes (Higher “dislike” tendency)	0	0	1	15	15	15
No changes (No higher “like” or “dislike” tendency)	2	5	0	0	0	0
Total no. of comments significantly affected by its higher “like” or “dislike” tendency	13/15	10/15	14/15	15/15	15/15	15/15

B. *Sentiment tools analysis*

Table 8 presents the results of sentiment analysis of positive comments using sentiment tools. Overall, the results suggest that 41% of tested sentiment tools showed no difference in scores between the original comment and its simulated counterpart. Such results indicate that these tools do not detect any change in sentiment value for comments with repeated letters. In other words, 41% of these tested tools do not consider letter repetition as an indication for a change in their sentiment score. For instance, Sentaero (Tool 2) gave a 100% positive result for both comments. Similarly, Meaning cloud (Tool 3) and Repustate (Tool 5) respectively showed positive results.

The remaining 59% of the tools showed different sentiment scores between the original comment and its counterpart. However, many of these tools gave different scores due to their inability to identify the word with repeated letters. For example, Selasdia Intelligent Sales Assistant (Tool 1) gave overall polarity to the comment by breaking down sentences and words. The comment “love our new tv” is marked as positive with word “love” given a positive polarity. However, “loooooove our new tv” is given a neutral polarity with zero sentiments, indicating that Selasdia Intelligent Sales Assistant is not able to detect the word “ loooooove”. Hence, the sentiment for this word changed from positive to neutral. Another example is Text sentiment analyzer (Tool 6), which gives score breakdowns for each word. The word “love” has a sentiment score of 0.5 but when letter repetition is added, the word “loooooove” is not on its list of sentiment-by-word.

There is no sentiment value assigned to this word. Another tool, Twinword (Tool 25), assigned a positive score of 0.917220858 to "love" but zero score to "looooooove". To sum up, although a majority of these tools gave different scores for the original comment and its simulated counterpart, the score difference is mainly due to the tools' lack of ability to detect the word with repeated letters. Changes in sentiment score are due to fewer words in the text (when tools are unable to detect the word with repeated letters) and not because letter repetition carries a special sentiment value. The only tool that is an exception to this is IMDB (Tool 14), which is able to spot the difference in a word between the original comment and simulated comment and increased the sentiment score for the word with repeated letters.

Table 8
Results of Sentiment Tools Comparison for Positive Text

Tool	Scores for original comment	Scores for simulated comment	Tool	Scores for original comment	Scores for simulated comment
1	P	P/N	17	P:+0.881	P:+0.877
2	P 100%	P 100%	18	P: 0.398052	P: 0.381061
3	P 98%	P 98%	19	P: 99.9658	P: 99.9376
4	P:0.922 NU:0.078	P:0.948 NU:0.052	20	P: 0.994583	P: 0.994583
5	0.95	0.95	21	Anger 0.002273 Disgust 0.00381 Fear 0.00381 Joy 0.954265 Sadness 0.02287	Anger 0.004542 Disgust 0.008128 Fear 0.006935 Joy 0.914345 Sadness 0.031392
6	P:40%	P:38%	22	P 100%	P 100%
7	P:9	P:9	23	P	P
8	P:3 N: -1	P:4 N: -1	24	Afraid:0.125 Amused:1 Annoyed:0.513 Dont care:0.931 Happy:0.645 Inspired:0.878 Sad:0.28	Afraid:0.149 Amused:1 Annoyed:0.541 Dont care:0.94 Happy:0.637 Inspired:0.805 Sad:0.274
9	Overall:P P:0.9 N:0.1	Overall:N P:0.8 N:0.2	25	P: 0.42613400582143	P: 0.22898918957143
10	Overall:3.29	Overall:3.29	26	P:92% N:8%	P:91% N:9%
11	Overall: 1.75	Overall: 1.5	27	Joy 0.95	Joy 0.91
12	3	2	28	Whole text is P	Whole text is P
13	8	6	29	Whole text is P	Whole text is P
14	Overall: 0.764	Overall: 0.905	30	Whole text is P	Whole text is P
15	P: 16.7	P: 12.5	31	"loooooove our new tv" is P "the tv is so light and thin it has a great picture and the colors are true very happy customer" is N	"loooooove our new tv" is P "the tv is so light and thin it has a great picture and the colors are true very happy customer" is N
16	P 100	P 100	32	Whole text is N	Whole text is P

Table 9 presents the results of sentiment analysis of negative comments using sentiment tools. Overall, the results suggest that 53% of sentiment tools showed no difference in score between the original comment and simulated comment. Sentiment tools such as Selasdia Intelligent Sales Assistant (Tool 1), Sentaero (Tool 2), Meaning cloud (Tool 3), Repustate (Tool 5), ParallelDots (Tool 23), and others showed similar results for both original and simulated comments. For instance, Repustate and Alchemy Language Document Sentiment (Tool 20) gave negative sentiment scores of -0.95 and -0.894785 respectively to the original comment and the simulated comment. Other tools such as Alchemy Language Targeted Emotion (Tool 21) and DepecheMood (Tool 24) treated the word with repeated letters as a spelling mistake.

The remaining 47% of the tools showed different scores between the comments. However, this score difference is due to the tools' inability to recognize the word with repeated letters. Interestingly, IMDB (Tool 14) differentiated "love" and "looooove" in the positive comment but it could not detect "haaaaaated" in the negative comment. Twinword (Tool 25) gave the word "hate" a negative sentiment score of -0.918459669 but no score for the word "haaaaaated". Additionally, some tools like Sentiment Vivekn (Tool 19), Tone Analyzer (Tool 27), and Pythia Semantic Features (Tool 28) showed different scores for both comments without giving a breakdown or detailed analysis of the score. However, as the score became less negative for the simulated comment, it can be assumed that these tools are also unable to detect the word with repeated letters.

Table 9
Results of Sentiment Tools Comparison for Negative Text

Tool	Scores for original comment	Scores for simulated comment	Tool	Scores for original comment	Scores for simulated comment
1	N	N	17	NU: +0.411	N: -0.153

2	N 100%	N 100%	18	N: -0.7	N: -0.5
3	N 100%	N 100%	19	N: 99.9104	N: 73.0657
4	N:0.938 NU:0.062	N:0.941 NU:0.059	20	N: -0.894785	N: -0.894785
5	N: -0.95	N: -0.95	21	Anger 0.639612 Disgust 0.00381 Fear 0.217572 Joy 0.186902 Sadness 0.018071	Anger 0.480416 Disgust 0.245976 Fear 0.254317 Joy 0.041167 Sadness 0.34586
6	N: 70%	N: 50%	22	N: 50% NU: 50%	N: 50% NU: 50%
7	N: 10	N: 10	23	N	N
8	P:1 N: -4	P:2 N: -4	24	Amused: 1 Angry: 0.26 Annoyed: 0.227 Dont care: 0.386 Happy: 0.649 Inspired: 0.605 Sad: 0.548	Afraid: 0.164 Amused: 1 Annoyed: 0.193 Dont care: 0.32 Happy: 0.762 Inspired: 0.629 Sad: 0.661
9	Overall:N P:0.1 N:0.9	Overall:N P:0.2 N:0.8	25	N: -0.20522453125	N: -0.1381325554
10	Overall: -4.976	Overall: -4.976	26	P:3% N:97%	P:2% N:98%
11	Overall: -0.125	Overall: -0.125	27	Anger 0.64 Analytical 0.6	Analytical 0.6
12	-2	-1	28	Whole text is N	Whole text is N
13	-1	-1	29	"i hated this iron because the steam co mes out in all the wrong places" is N "i burnt my fingers a lot" is P	i "i haaaaaated this iron because the steam comes out in all the wrong places" is N "i burnt my fingers a lot" is P
14	Overall: -0.0302	Overall: 0.0918	30	Whole text is N	Whole text is N
15	N: 10.0	N:5	31	Whole text is N	Whole text is N
16	N -100	N -100	32	Whole text is N	Whole text is N

V. Conclusion

The current study examines the impact of letter repetition on perceived sentiment expression in online product reviews, as assessed by both individual participants and sentiment tools. Based on a collection of 30 online comments that were manually classified into positive or negative sentiments by 500 individual participants results revealed that letter repetition indeed affects readers' perceived sentiment connotation of the comments. Letter repetition has a particularly greater augmenting effect on negative comments than positive comments.

On the other hand, the results of sentiment tools suggest that many of them are unable to detect words with repeated letters. This indicates that developers should pay more attention in fine-tuning these tools in analyzing the sentiment value of repeated letters. This study's findings imply that automated social media analysis systems, such as sentiment analysis tools, should take into account letter repetition in social media messages for a more accurate and efficient analysis and extraction of opinions of consumers and other users in general. The study's human-rated dataset will be made publically available with the paper under a creative commons license.

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